

# Risk Transfer Policies Facilitate Smallholder Farmer Climate Adaptation

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## Abstract

Increasing climate stress is likely to significantly impact smallholder farmer livelihoods, and can lead to divergent adaptation pathways. However, empirical evidence is inconclusive regarding how climate affects smallholder farmers' deployment of various livelihood strategies, including rural-urban migration, especially as these impacts become more severe. Here we use an agent-based model to show that in a South Asian-type agricultural community experiencing a 1.5°C temperature increase by 2050, climate impacts are likely to decrease household income in 2050 by an average of 28 percent relative to the same income under a stationary climate, with fewer households engaging in economic migration and investing in cash crops. Pairing a small cash transfer with risk transfer mechanisms significantly increases the adoption of alternative livelihood strategies, improves community incomes, and reduces community inequality. While specific results depend on contextual factors such as risk preferences and climate risk exposure, these interventions are robust in improving adaptation outcomes by addressing the intersection of risk aversion, financial restrictions, and climate impacts.

## 1 Introduction

Climate change is likely to impact the livelihoods of many of the world's 500 million smallholder farming households [1, 2], particularly with projected increases in drylands populations [3]. Migration represents one of several adaptation strategies that farmers could deploy in the face of climate stress [4], and there is mixed evidence on the extent to which climate change may positively or negatively impact migration flows [5–12]. While some studies warn that climate impacts could displace over 100 million people worldwide [13, 14],

scholarship from more traditional migration disciplines emphasizes that climate change may constrain various forms of resources needed to migrate, including financial and social resources [8, 15, 16]. Furthermore, uncertainty regarding future climate adaptation policies at multiple governance scales [17], including new financial instruments that could help poor households better cope with natural disasters [18–20], further cloud projections about how climate change will impact rural households' use of migration as a risk management strategy. Conversely, policymakers seeking to promote climate resilience need to better understand the complex ways in which potential interventions may impact the dynamics of household adaptation decisions. This study seeks to better understand how rural-urban migration relates to other on-farm adaptation strategies and risk-transfer mechanisms as smallholder farming households cope with increasing climate stress.

While previous econometric studies have built our understanding of the conditions under which climatic factors have influenced migration patterns [5, 6, 11, 12, 21], they typically have limited ability to account for dynamic interactions between changing climatic and societal variables [22]. Recently, experimental economics has elucidated some causal factors of climate migration decisions [23], but under a limited set of conditions. One additional set of tools for investigating these questions includes agent-based models (ABMs). ABMs simulate how individual decision-makers (generally at the person or household level) make choices based on pre-defined decision-making rules, complex interactions between agents, and feedbacks between agent actions and their environment [21, 24]. Recent climate-migration ABMs have explored non-linear feedbacks between migration decisions and dynamic push-pull factors, including changing environmental conditions [25–30] (see SI Section 1 for more details). However, previous scholarship has not yet systematically analyzed the impact of risk-transfer mechanisms on climate adaptation strategies of rural households, for several reasons. First, some ABMs condition migration decisions based on previous statistical relationships [25, 26], rather than embedding these decisions as part of a generalizable decision-making framework for livelihood strategies that accounts for multiple adaptation options. Second, some models impose an arbitrary set of climate shocks (e.g., forcing their models through droughts in predetermined years) rather than relating the probability of extreme events to broader climate scenarios of temperature and precipitation change [27–29]. Finally, with the exception of Bell et al. [30], ABMs have not explored the possible effects of risk transfer mechanisms, either through informal networks or formal government policies, on household decisions.

Based on these gaps, this study seeks to address three main research questions. First, how does increased climate stress impact livelihood strategy choices of smallholder farmers over time? Second, what decision-making factors (e.g. societal risk preferences, financial restrictions) have the most impact on these adaptation pathways? Third, how are various risk-transfer mechanisms likely to impact adaptation outcomes for smallholder farmers?

## 2 An Agent-Based Model to Simulate Farmer Livelihood Decisions

To address these questions, we developed an ABM that examines climate adaptation decisions among smallholder farming households. The ABM features multiple livelihood strategies, including on-farm adaptation and rural-urban migration. Farming households, which serve as the main decision-making agents, form perceptions about the expected income and risk of each strategy based on their interactions in a small world-type social network. Households select livelihood strategies based on a consistent decision-making framework, subject to the constraints of financial limitations (Fig. 1). We model the impact of increasing climate stress on these decisions, including both long-term changes in crop yields due to rising temperatures, and time-varying probabilities of extreme droughts.

The ABM consists of  $N$  agents in a farming community, each representing a household consisting of 5 working-age people. At each time step, households can either farm low-risk, low-cost and low-reward cereal crops (e.g. rice or maize) in the Business-as-Usual (BAU) strategy, or farm higher-risk, higher-cost, and higher-reward commercial crops (e.g. legumes and fruits) in the Diverse strategy. In either case, households can also decide to: (a) deploy up to 1 additional migrant per cropping cycle who can earn remittances, (b) leave their migration status unchanged from the previous time step, or (c) return up to 1 migrant back to the farm. This creates 11 distinct strategy options for households: farming BAU crops while sending between 0 - 4 migrants; farming Diverse crops while sending between 0 - 4 migrants, or sending all 5 working-age members as migrants. For each migrant, households pay an initial up-front cost in the first time step of migration, and receive remittances with high reward and high risk starting from the second time step. While simplified, these options are meant to represent a broader suite of smallholder farming livelihood choices that differ based on their expected income, income volatility, and up-front costs (see Methods for decision-making utility function and SI Section 2 for how these entities are parameterized).

Along the lines of pattern-oriented modelling [31], the ABM is built in four layers of increasing complexity representing rational decision-making, bounded rationality and social network effects, demographic stratification, and climate effects (Methods). We use the ABM to evaluate the dynamics of several community outcomes of interest, including: the final distribution of household strategy choices, the average community income, proportion of the community that migrates, the GINI coefficient, and the proportion of households whose savings are less than the cost of migration (which we term the "immobility threshold").<sup>1</sup> The most relevant model parameters affecting mentioned output

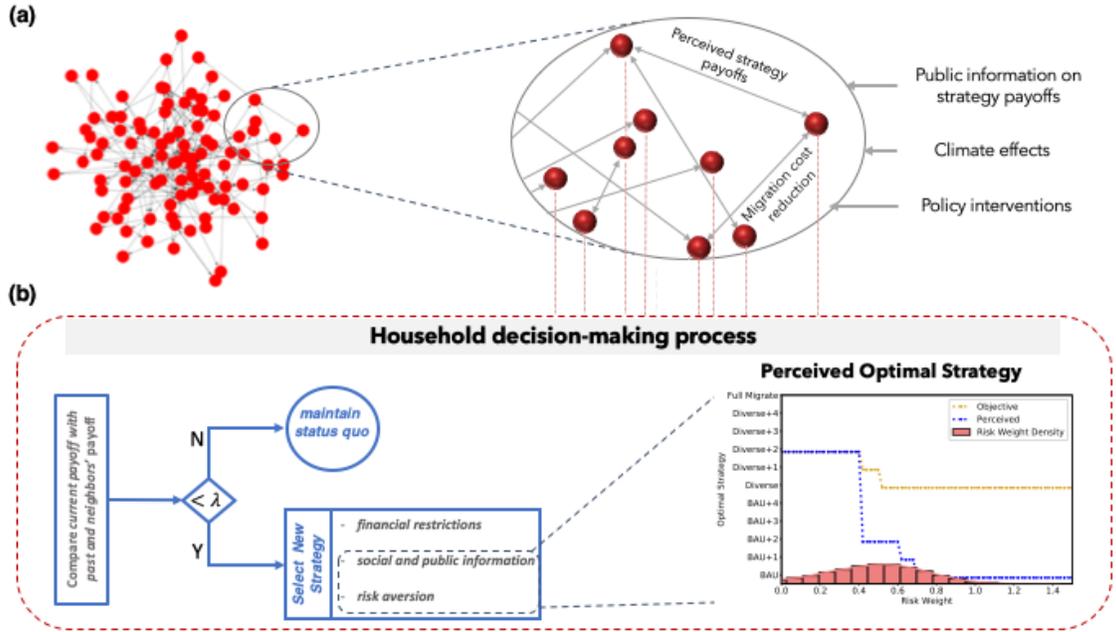
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<sup>1</sup>Note that this analysis focuses on planned migration that is primarily motivated by economic opportunity; we do not include socio-cultural migration (e.g. for marriage or amenity reasons) or distress migration that might occur as an option of last resort. This latter category of migration is also of interest to policymakers, and may follow different patterns from the results presented here.

variables are the status-quo parameter  $\lambda$  indicating when the current household strategy needs to be re-evaluated, the risk aversion  $b_i$  penalizing income volatility, the information preference parameter  $\omega_i$  balancing social versus public information sources, the household memory length  $m_i$  affecting the perceived income and volatility of different strategies, and the temperature increase  $\Delta T$ . Heterogeneity between households is included in the ABM, indicated by the index  $i$  corresponding to each household in the farming community. Figure 1 illustrates the main conceptual features of the model, from the community scale to individual decision-making parameters.

We create this model to derive generalizable insights regarding the intersection of key climate, economic, and decision-making processes that are likely to shape smallholder farmer climate adaptation across a variety of contexts. Therefore, we do not claim to represent the adaptation outcomes of a particular region with complete accuracy. However, to ground the model in some policy-relevant context and partially demonstrate its validity, we seed the model with a variety of climate and socioeconomic data from South Asia. Smallholder farming villages in this region tend to exhibit several shared characteristics that make it especially relevant to this study: (1) rainfed, smallholder agriculture is currently the main livelihood option [1, 32], (2) alternative livelihood options (e.g. cash crops and migration) tend to be costlier and riskier than subsistence farming [33], and (3) future climate change is likely to decrease crop yields across most non-mountain regions, threatening the viability of current farming livelihoods [34].

In the Base Case application of the model, we employ economic data collected between 2006-2015 from the Chitwan Valley Family Study (CVFS) in Nepal [35] to characterize the mean and variance of income generated from each strategy option, and conduct partial validation based on previous household strategy choices that were observed in this survey (SI 3.3). Average seed and labor costs in Nepal for each type of farming strategy were obtained from Katovich and Sharma [36] and Nepali emigration costs were estimated from Shreshta [37]. Risk aversion of decision-making agents is based on the distribution of Nepali tea farmers' risk aversion as measured by Mohan [38]. The model is initialized using CVFS data on the distribution of households by livelihood strategies in 2007 and run for 44 years to 2050, with two time steps per year in which households can update their strategy decisions (representing major cropping cycles). We assume an increase  $\Delta T = 1.5^\circ C$  from 2006-2050, consistent with the mean of Coupled Model Intercomparison Project (CMIP) 6 projections for South Asian region [39], and correlate temperature increase with changing crop yields [40] and probability of extreme drought [41] (Methods). To assess the robustness of our conclusions, we also conduct a series of sensitivity analyses to key parameters (SI 3.4), and explore two alternative scenarios that differ based on the degree of climate risk and community risk aversion.



**Figure 1: Schematic overview of ABM structure.** (a) Households are arranged in small-world networks where the number of neighbours follows a power law with mean  $\bar{j}$ . Households within this structure interact by observing the strategies and incomes obtained by each of their neighbors, and of their own household, over the past  $m$  cropping cycles in their memory. Households combine this social network information with information obtained from public sources, which we assume to provide perfect information on mean and variance of strategy incomes, weighted by the information preference parameter  $\omega_i$ , following a normal distribution with mean value  $\bar{\omega}$ . Migrants from one household also reduce costs for other potential migrants from the households to which they are connected. In the climate layer of the model, we include (i) a long-term decline in crop yields due to temperature increase  $\Delta T$ , and (ii) an increased frequency of extreme droughts as a function of  $\Delta T$ . Various policy options are introduced that impact the expected income and/or variance of the considered strategy options. (b) Each cropping cycle, households either pursue their status quo strategy if their profit differentials, established with respect to their  $m$  past profits and that of their neighbours, are above a reference point  $\lambda$ , or otherwise deliberately select a new strategy. These decisions are made through a utility function that includes the perceived expected income and standard deviation of each strategy option, balanced by the household risk weighting and constrained by the household financial assets (Method section).

## 3 Results

### 3.1 Sources of Immobility in Climate Adaptation

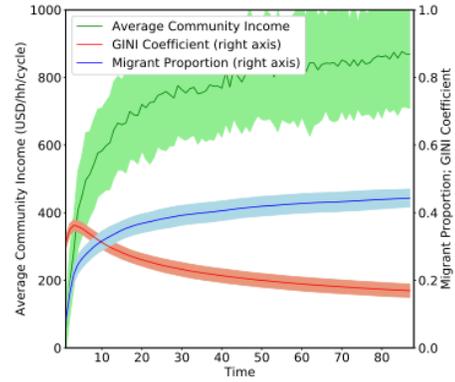
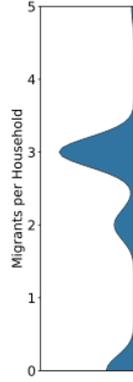
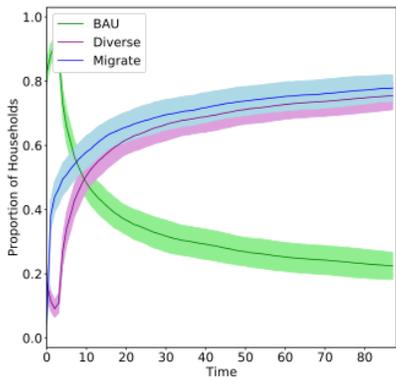
The layered structure of the ABM allows us to disaggregate differential effects of financial restrictions, bounded rationality, demographic stratification, and climate stress on household livelihood strategies and adaptation outcomes (specifically: average household income, proportion of the community that migrates, and inequality in household incomes as measured by the GINI coefficient). Under complete economic rationality (i.e., households optimize expected profit under perfect information, constrained by financial assets), 75 and 78 percent of households opt for the Diverse and Migrate strategies, respectively, by terminal time (Fig. 2a, left). This does not happen immediately - households must first accumulate sufficient resources to afford the costs of these alternate strategies. The vast majority of households (60 percent) ultimately send three migrants (centre), while keeping two household members to pursue Diverse farming, to optimize their household income. The average community income rises to approximately 870 USD/household/cropping cycle, and 44 percent of the community's working-age population migrates by the end of the model run (right). Because the same strategy options are adopted by most households, the GINI coefficient drops to 0.17.

Bounded rationality characteristics (i.e., risk aversion and partial reliance on one's social network for information) decreases the proportion of households that adopt Diverse and Migrate strategies to 45 and 70 percent of households, respectively, by terminal time (Fig. 2b, left). Due to the reliance on strategy income assessments present in the social network, households have varying perceptions of strategy income and volatility (SI 3.2). Households also penalize the perceived volatility of each strategy, which reduces the attractiveness of the Diverse and Migrate strategies relative to BAU. While most households continue to engage in some migration, the majority now send 2 or less migrants per household (centre). This significantly decreases average income to approximately 610 USD/household/cropping cycle, and lowers the overall migrant population (right).

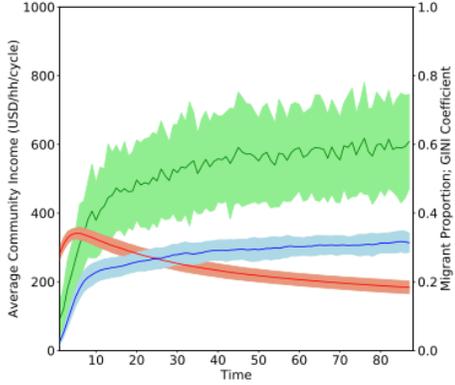
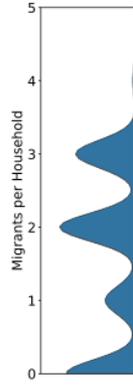
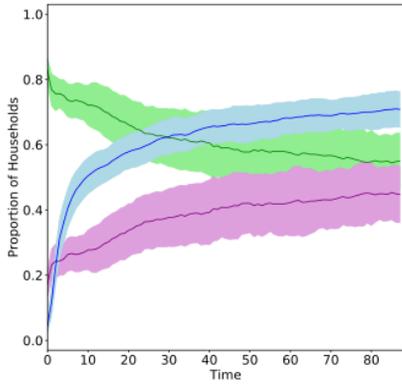
The stratification of the population by educational attainment further depresses the adoption of the Diverse and Migrate strategies to 42 and 58 percent of households, respectively (Fig. 2c, left). Here, the correlation of lower wealth, higher risk aversion, and less access to objective information creates significant disparities in the strategy choices between the different educational classes of agents (SI 3.1). This is primarily true for households with primary education: poor access to information, higher risk weighting, and lack of financial resources combine to keep the majority of smallholder farming households in the relatively low-income, low-risk BAU strategy, while more elite groups of the community take advantage of higher-risk, higher-cost, and higher-return strategies. Demographic stratification further decreases average income to 530 USD/household/cycle (right), and leads to a significantly higher GINI coefficient of 0.25 by terminal time.

Climate effects, representing a  $1.5^{\circ}\text{C}$  increase in mean annual temperature by 2050, further depress the adoption of the Diverse strategy to 19 percent of households by terminal time, and lowers migration to 52 percent of households (Fig. 2d, left). Owing to decreased crop yields and increased extreme droughts, some households switch back from Diverse to BAU crops (especially after  $t = 50$ , approximately corresponding to the year 2032). As the Diverse strategy represents farming water-intensive cash crops, increasing climate stress renders this a riskier strategy due to its increased exposure to extreme drought. Additionally, the negative effect of climate stress on both Diverse and BAU crop yields make it more difficult for households to accumulate sufficient resources to afford the up-front cost of migration. These financial restrictions stem the growth in migration that occurs in later time steps in scenarios without climate effects. While fewer households overall engage in migration, a few households who have sufficient assets ultimately send additional migrants by terminal time (centre). At the community level, climate stress further lowers average income by 28 percent compared to the scenario without climate effects, to 380 USD/household/cycle (right), and slightly increases the GINI coefficient to 0.27, while the overall migrant proportion remains unchanged at 24 percent of the community. As this final layer is intended to be the most representative of real-world complexity, we use this as the basis for a partial validation of the model (SI 3.3).

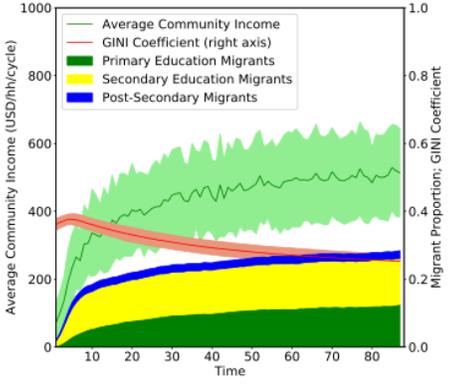
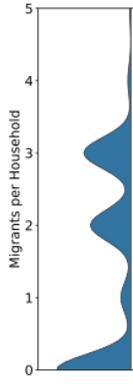
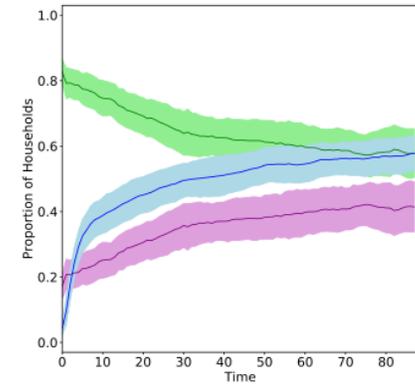
**(a) Economic Rationality Layer**



**(b) Bounded Rationality and Social Network Impact**



**(c) Demographic Stratification**



**(d) Climate Impacts**

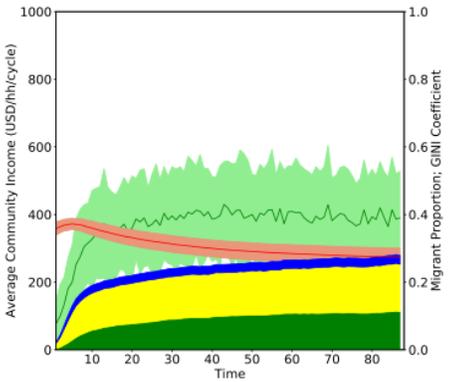
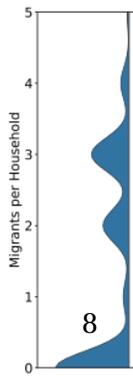
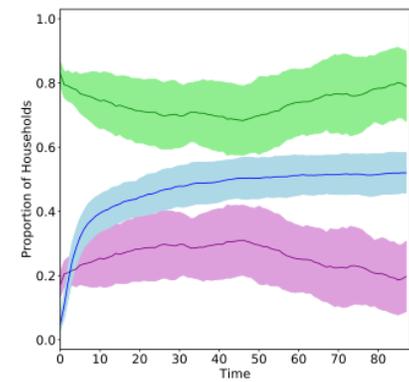


Figure 2

**Figure 2:** (Previous page.) **Evolution of Household Strategy Choices and Community Outcomes under Four Model Layers.** **(a)** Under Economic Rationality, the vast majority of households adopt both Diverse and Migrate strategies over the course of the model timeframe (left), and most deploy 3 of their 5 working-age members as migrants (centre). These strategies lead to a steadily increasing average community income over time (green line, right), while the proportion of community migrants also increases as more households gain financial resources to afford this strategy (blue line). **(b)** The introduction of Bounded Rationality and Social Network effects decreases the adoption of Diverse and Migrate over time, decreases the average number of migrants per household, and limits the growth in average income and migration proportion. **(c)** Stratification of risk weighting, information access, and financial resources along educational lines further reduces the proportion of households who adopt Diverse and/or Migrate, while most households that engage in Migrate generally send 2 or 3 migrants. Although primary-educated households make up 65 percent of the community, over 63 percent of migrants come from households with secondary or post-secondary educational attainment (yellow and blue shaded regions, respectively, in right-hand panel). **(d)** With a 1.5<sup>0</sup>C temperature increase over the considered time horizon, the proportion of households switching to Diverse crops is limited, and decreases after about  $t = 50$ . The majority of households do not engage in migration, while those that do send 2-3 migrants. This further lowers average community income, and increases community inequality. Results for each plot represent average values for each time step over 100 model simulations; shaded values indicate +/- 1 standard deviation.

### 3.2 Risk Aversion and Financial Restrictions Mediate Climate Adaptation Outcomes

While Nepal’s Chitwan Valley serves as a Base Case to illustrate and partially validate our model, community risk preferences, financial limitations, and the degree of expected temperature change may vary widely across South Asian farming communities. Notably, recent estimates from CMIP 6 indicate that South Asian countries are likely to experience mean annual temperature increases between  $1 - 3^{\circ}\text{C}$  by 2050 [39]. Smallholder farmer risk preferences have also been shown to vary widely across South and Southeast Asia, between risk neutrality (i.e. solely optimizing on expected income) and high risk aversion (i.e. high preference for avoiding uncertain outcomes) [38, 42, 43]. Here we show how these two parameters ( $b_i$  and  $\Delta T$ ) interact with financial constraints to mediate climate adaptation outcomes. In particular, the proportion of the community that engages in labor migration varies widely for different combinations of risk aversion and degrees of temperature change, from 0 to 50 percent of the community (Fig. 3d). Generally, higher values of average community risk aversion  $\bar{b}$  result in lower community migration, as this strategy involves a significant degree of income volatility. The relationship between temperature change and migration is more complex. There is a clear positive relationship between temperature and labor migration for communities with relatively low average risk aversion (roughly  $\bar{b} < 0.5$ ); in this range, increases in temperature change lead to higher community migration. However, there is no clear relationship between temperature and labor migration for higher values of average community risk aversion (roughly  $\bar{b} > 0.5$ ): the effect of risk aversion on migration is dominant, regardless of values of  $\Delta T$  even beyond the range of expected temperature changes for the region [39]. This reflects complex interactions between temperature change, risk aversion, and financial limitations in the context of alternative risky livelihood strategies.

We illustrate these interactions through three example scenarios that explore different potential combinations of risk aversion and climate risk exposure in South Asia: (A) a high risk ( $\Delta T = 4.5^{\circ}\text{C}$ ), low community risk aversion ( $\bar{b} = 0.25$ ) scenario; (B) our Base Case, reflecting a relatively low risk ( $\Delta T = 1.5^{\circ}\text{C}$ ), medium risk aversion ( $\bar{b} = 0.5$ ) scenario; and (C) a medium risk ( $\Delta T = 3.0^{\circ}\text{C}$ ), high risk aversion ( $\bar{b} = 1.25$ ) scenario. For each scenario, we progressively quantify the relative effects of each model layer on the proportion of community migrants (Fig. 3a-c), as well as other outcome variables of interest (SI 3.5), relative to a counterfactual model that includes all the previous layers of complexity. We also compare the effect of these layers in a model where households adopt their preferred strategies without financial constraints relative to the model where households must be able to afford the up-front cost of alternative strategies. This allows us to quantify the added effect of financial restrictions for each model layer.

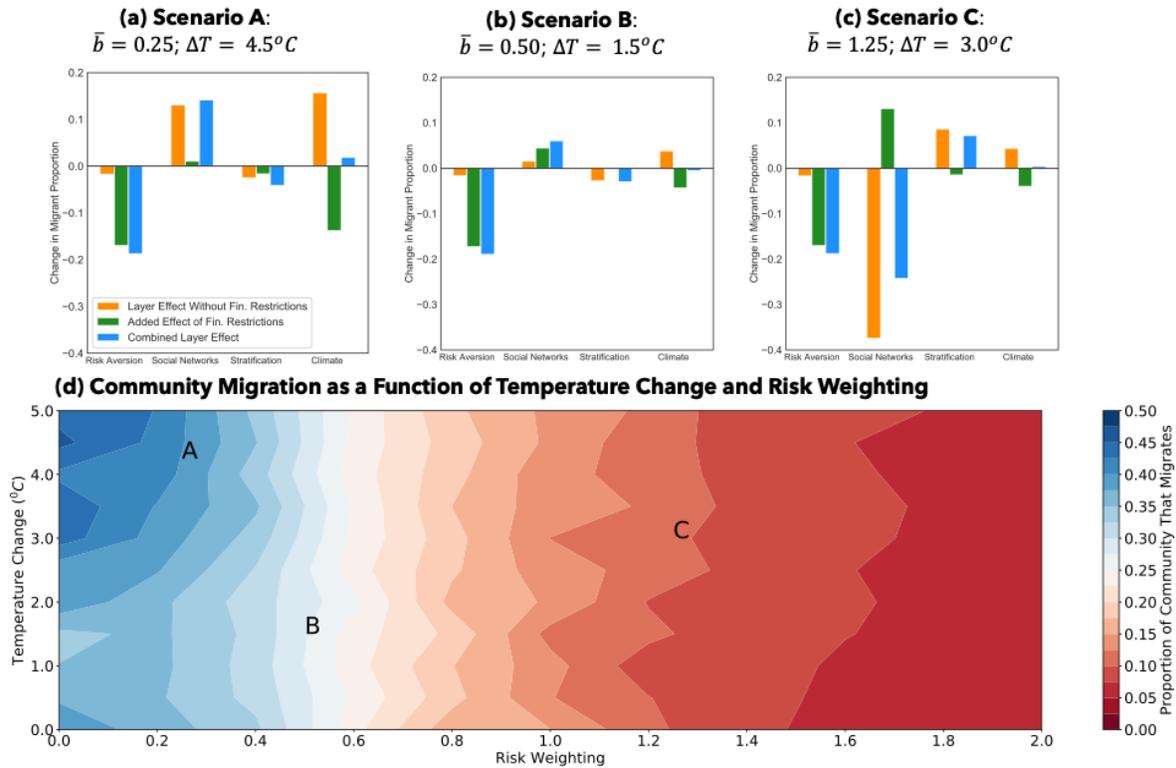
The specific effects of each model layer vary across these scenarios. For example, the impact of social networks ranges from significantly increasing migration in Scenario A to significantly decreasing migration in Scenario C. This reflects two mechanisms by which

social networks influence migration outcomes: (1) they serve as conduits for households to establish reference points for updating strategies and to exchange information on strategy profits, and (2) they reduce migration costs for households connected to migrants. Under high risk aversion, the first effect predominates, and households tend to remain with the BAU strategy. Under low risk aversion, the second effect predominates, and social networks facilitate migration.

Despite significant variation across scenarios, two robust relationships emerge. First, the combination of risk aversion and financial restrictions consistently drives down the use of migration as an adaptation strategy, which decreases average community income (SI 3.5). This relationship works through a direct channel, in which risk aversion reduces the perceived utility of high-risk migration, and also indirectly, in which risk aversion decreases the adoption of the relatively risky Diverse strategy, preventing some households from accumulating sufficient resources to afford migration.

A second robust pattern is that in the absence of financial restrictions, climate impacts would consistently lead to an increase in community migrants relative to a counterfactual without climate impacts. As climate impacts progressively reduce expected income from the farming strategies while increasing their volatility through extreme droughts, households increasingly perceive migration as a preferred strategy. However, financial restrictions attenuate this effect and prevent some households from affording the initial migration cost, while also preventing some households from switching to Diverse crops and accumulating resources to migrate through this channel. The net directional effect depends on complex interactions between the degree of climate risk, the average community risk aversion, and the degree to which financial restrictions prevent households from pursuing the Diverse and Migrate strategies prior to the manifestation of climate effects. Similar to other studies that investigate sources of immobility in the face of climate risk [8, 44], we find that some individuals who would otherwise migrate in the absence of financial constraints are in fact rendered immobile by such restrictions.

The complex interactions between climate risk, community risk aversion, and financial restrictions can serve as further explanatory factors for divergent migration patterns in the face of climate risk [12], particularly when there are multiple adaptation options with different risk-reward profiles. On the other hand, the robust effects of risk aversion and financial limitations on reducing community migration and average income suggest a role for risk transfer policies and interventions such as cash transfers that help households overcome financial restrictions.



**Figure 3: Drivers of Migration Outcomes for Different Risk and Climate Scenarios.** Model outcomes are driven by complex interactions between financial restrictions and several decision-making drivers in the model, shown here for three distinct scenarios. Each panel demonstrates the effect of the specified model layer on the proportion of the community that migrates in the absence of financial restrictions (orange), the additional effect of financial restrictions for this layer (green), and the net combined effect of the layer with financial restrictions (blue). **(a)** In Scenario A, risk aversion significantly reduces community migration, while the presence of social networks significantly increases community migration, relative to previous model layers. In the absence of the financial constraint, climate effects would lead to a more than 15 percentage point increase in community migrants, but this is mostly attenuated by the presence of financial restrictions, for a net increase of 3 percentage points in the migration rate. **(b)** In Scenario B, risk aversion substantially drives down migration, again exacerbated by financial restrictions. Social networks somewhat increase migration. In the absence of financial restrictions, climate effects would increase migration by 4 percentage points, but financial restrictions actually lead to a net decrease in migration of 1 percentage point. **(c)** In Scenario C, both risk aversion and social networks significantly reduce the migration rate. Without restrictions, climate effects would increase migration by 5 percentage points, but this is mostly erased by the presence of financial restrictions. **(d)** The intersection of different community average risk weighting  $\bar{b}$  and the degree of temperature change  $\Delta T$  leads to different outcomes for the proportion of the community that migrates.

### 3.3 Risk and Cash Transfer Policy Packages Robustly Improve Community Outcomes

Smallholder farmers do not make decisions in a vacuum: policymakers at various governance scales can design incentives to influence farmers' perceived risk of various livelihood strategy choices, as well as their capacity to implement such strategies. Here we assess the impact of three such policy interventions: index-based insurance, a remittance bank that smooths volatility in migrants' income, and cash transfers. Each of these interventions has been implemented in real-life contexts in South and Southeast Asia (for examples, see [18, 45] for index-based insurance; [46] for remittance banks; and [47] for cash transfers, among others). In this model, we assume that such interventions are generally implemented at the national scale, but we focus our analysis on how they impact community-scale outcomes. Specifically, we assess their impacts on average community income, inequality as measured by the GINI coefficient and the number of households below an immobility threshold (Fig. 4); and overall community migration (SI 3.6).

The impacts of these policies are assessed for the three illustrative scenarios described above. As a way to compare each policy on a relatively equal footing, we assume that the government allocates a total of 30 USD/household/cycle to spend on interventions; this budget is roughly in the same range as existing cash transfer schemes in Nepal [47], as well as existing government subsidies for an index insurance program [45]. Thus, our three policy options are: (1) an unconditional cash transfer of 30 USD/household/cycle, (2) index-based insurance that is offered with a 30 USD/hh/cycle subsidy on an actuarially-fair premium; or (3) a remittance bank that offers a 30 USD/cycle subsidy for households that engage in migration. We also examine the combination of all three interventions (a 30 USD/hh/cycle cash transfer with non-subsidized insurance and remittance bank) to assess the potential for a policy package that addresses both financial restrictions and risk aversion. See Methods for more details.

While each intervention exhibits some potential to improve community outcomes relative to a no-policy baseline, one conclusion from our experiment is that the relative effectiveness of these three policies depends on the community risk preferences and exposure to climate risk. For example, in Scenario A, characterized by low risk aversion and high risk exposure, index insurance and cash transfers exhibit greater potential to increase average community incomes and reduce inequality by the end of the model timeframe, relative to the remittance bank (Fig. 4a). Under these conditions, migration is the most resilient livelihood strategy to such high climate risks, and the main obstacle to greater adoption of this strategy is not risk aversion, but rather financial restrictions that are exacerbated by increasingly frequent droughts. Both cash transfers and index insurance address these by either directly providing households with additional income (cash transfers), or protecting households against the erosion of financial assets due to droughts (insurance), enabling a higher proportion of households to engage in migration (Fig. 5a). By contrast, in Scenario C, characterized by high risk aversion and moderate climate risk exposure, the remittance

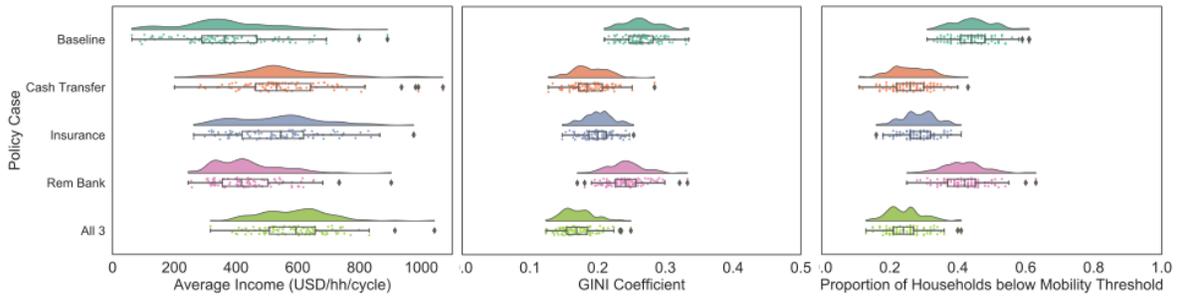
bank is the most effective individual policy in increasing average income while reducing the community GINI coefficient (Fig. 4c). Here, high risk aversion is the most significant obstacle to households adopting livelihood strategies, notably migration, that can help them adjust to increasing climate risk. A remittance bank most directly addresses this obstacle by reducing the variance associated with this strategy, increasing the proportion of households engaging in migration relative to other policies (Fig. 5c). In Scenario B, characterized by moderate risk aversion and low climate risk, each policy exhibits roughly equal ability to improve community outcomes (Fig. 4b). Under these conditions, both Diverse and Migrate are viable alternative strategies that improve community outcomes, and risk aversion and financial limitations are both significant obstacles to more households adopting these strategies. Each intervention addresses at least one of these barriers and leads to more households adopting either migration and/or diverse crops relative to the no-policy baseline (Fig. 5b).

One robust finding across all scenarios is that a combination of all three policies is always at least as effective, and often more effective, than any individual policy in increasing average income and reducing inequality. For example, in Scenario B, this policy package increases average household incomes by 88 percent relative to the no-policy baseline (352 to 660 USD/hh/cycle), while reducing inequality by 45 percent, as measured by the GINI coefficient. This policy package also has substantial impacts on increasing incomes and reducing inequality for Scenario A, and more limited, but still significant, effects on these outcomes in Scenario C. The consistent improvement in community outcomes suggests that under a variety of community risk preferences and climate risk exposure, policymakers seeking to promote climate-resilient livelihoods can exert the most leverage by pairing policies addressing financial limitations (i.e., cash transfers) with those transferring some risk from individual households to collective scales (i.e., index insurance and a remittance bank).

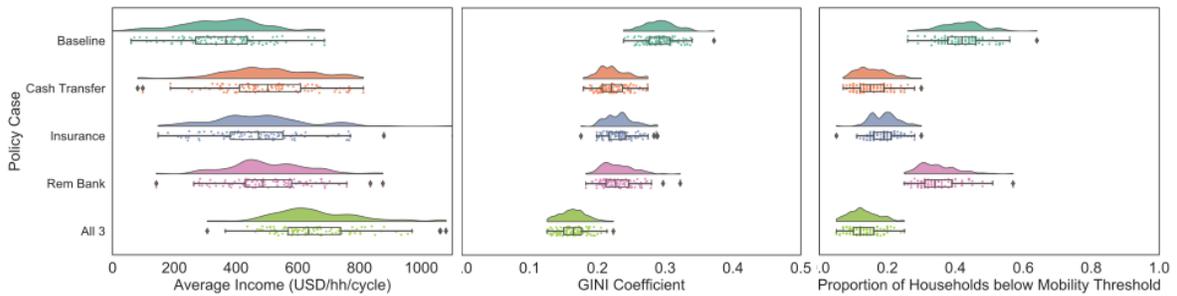
However, a second robust finding provides some grounds for caution in relying too heavily on risk transfer mechanisms to promote higher-risk climate adaptation strategies. In all three of our scenarios, the remittance bank leaves a significantly higher proportion of households with savings below an immobility threshold (the average up-front cost of migration without help from migrant networks) relative to the other policies. For example, in Scenario B, both insurance and cash transfers reduce the proportion of such households from 42 percent in a no-policy baseline to less than 20 percent, but the remittance bank still leaves 35 percent of households below such a threshold. Even in Scenario C, where the remittance bank is the most effective individual policy in reducing the GINI coefficient, it nonetheless leaves a higher proportion of households below this immobility threshold. Essentially, this policy creates two classes of households - those that are able to afford the upfront migration cost and thus benefit from this policy, and those that cannot reach this threshold and are left behind by the policy. This effect is sensitive to the cost of labor migration relative to the average income from BAU farming: a higher ratio would leave even more households below this immobility threshold, whereas a lower ratio would allow

more households to climb over this threshold and benefit from the remittance bank policy. Again, this finding reinforces the recommendation that policymakers consider packaging interventions that address risk transfer with those addressing financial restrictions to promote climate-resilient livelihood decisions.

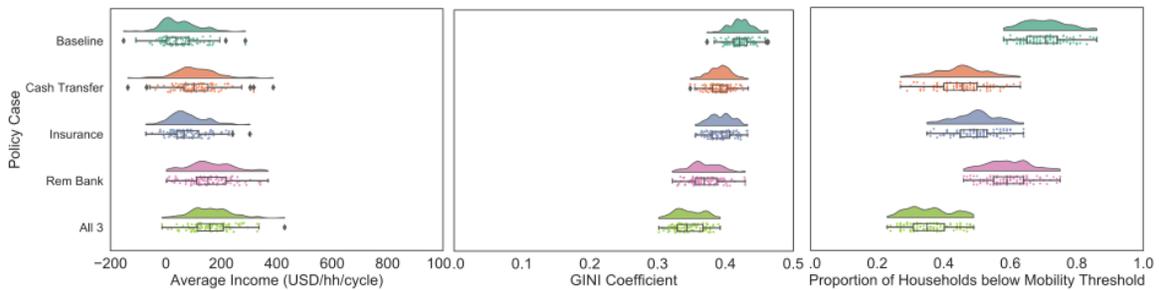
**(a) Scenario A:**  $\bar{b} = 0.25$ ;  $\Delta T = 4.5^\circ C$



**(b) Scenario B:**  $\bar{b} = 0.5$ ;  $\Delta T = 1.5^\circ C$

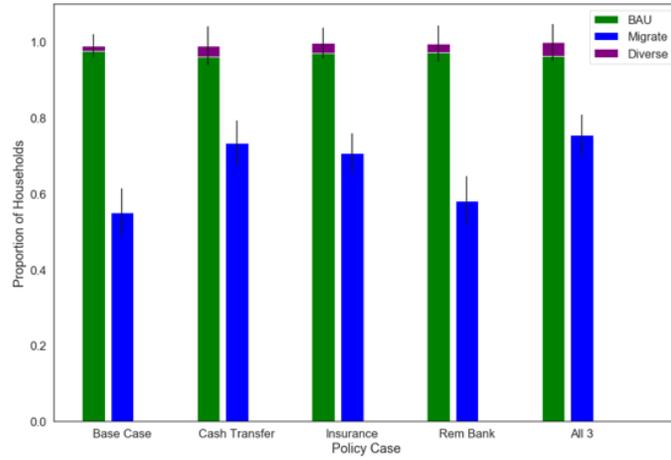


**(c) Scenario C:**  $\bar{b} = 1.25$ ;  $\Delta T = 3.0^\circ C$

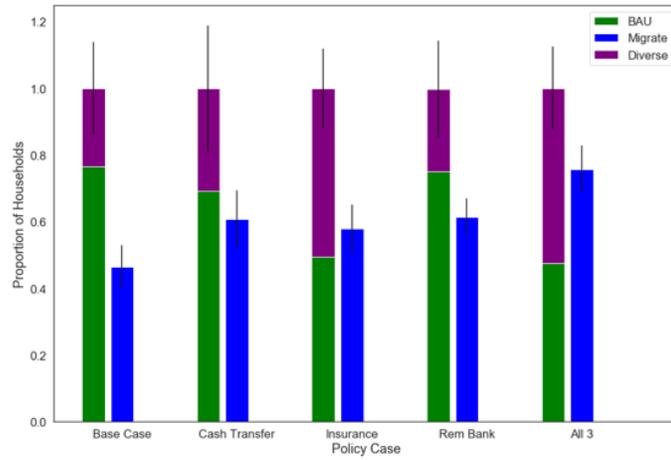


**Figure 4: Comparison of policy effects on community income and inequality under three scenarios.** Each panel demonstrates the distribution of community outcome metrics by model terminal time over 100 simulation runs (from left to right: average household income, community GINI coefficient, and proportion of households below an immobility threshold, i.e. the initial migration cost without assistance from migrant networks). For each panel, individual rows represent the effect of the policy condition specified on the y-axis. Dots indicate individual simulation outcomes, with the smoothed data distribution indicated above these dots; boxplots indicate the mean of the distribution and the interquartile range. **a)** In Scenario A (low risk aversion, high climate risk), cash transfer and index insurance demonstrate the best ability to increase average income, decrease the GINI coefficient, and reduce the proportion of households below the immobility threshold, relative to a no-policy baseline. **b)** In Scenario B (moderate risk aversion, low climate risk), all three policies demonstrate roughly equal abilities to increase average incomes and reduce inequality. **c)** In Scenario C (high risk aversion, moderate climate risk), the remittance bank demonstrates the best ability to increase average incomes and reduce inequality. Two robust findings are consistent across all three scenarios: a remittance bank by itself would leave more households below an immobility threshold relative to the other policies, and a package of all three policies leads to the highest average income and lowest inequality by these metrics.

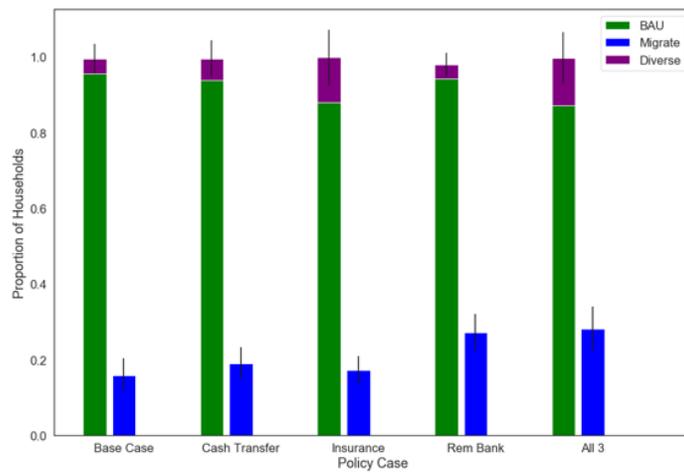
**a)**  $\bar{b} = 0.25; \Delta T = 4.5^\circ C$



**b)**  $\bar{b} = 0.5; \Delta T = 1.5^\circ C$



**c)**  $\bar{b} = 1.25; \Delta T = 3.0^\circ C$



**Figure 5**

**Figure 5:** (Previous page.) **Comparison of policy effects on final household strategy distributions under three scenarios.** Each panel demonstrates the average proportion of households deploying each strategy by terminal time against the left-hand y axis in green (households choosing BAU), purple (Diverse), and blue (Migrate) over 100 model simulations; error bars represent +/- 1 standard deviation. Results are shown for the no-policy baseline condition, index insurance, remittance bank, cash transfer, and a package of all 3 policies. Note that the proportions add up to more than 1 for each policy condition, as households may jointly pursue one farming strategy and Migrate. **a)** In Scenario A, the Index Insurance, Remittance Bank, and combination of All 3 policies significantly increase the proportion of households that pursue migration relative to the baseline. The Remittance Bank does not significantly alter household strategy choices relative to the baseline. **(b)** Under Base Case conditions (Scenario B), each policy significantly increases the proportion of households pursuing migration; the Index Insurance and combination of All 3 policies also significantly increase the proportion of households pursuing Migration. **c)** In Scenario C, only the Remittance Bank and combination of All 3 policies significantly increase the proportion of households engaging in migration, while the Index Insurance and combination of All 3 policies significantly increase the proportion of households pursuing the Diverse strategy.

### 3.4 Conclusions

Increasingly severe climate impacts are likely to challenge the viability of smallholder farmer livelihoods in the coming decades, forcing farming households and policymakers alike to make complex decisions. Several factors are likely to influence these decisions and their ramifications for climate adaptation outcomes, including climate risk exposure, community risk preferences, financial restrictions, access to information, and government incentives. To improve the efficacy of policies aimed at promoting resilient livelihoods, policymakers must account for non-linear interactions between these factors.

We note that several factors with the potential to influence smallholder farmers' climate adaptation responses are outside the scope of this study, and their intersections with these factors also merit further study. First, we do not explore the potential for climate change to impact future civil conflict, which may be a significant migration push factor [48]. Second, our analysis also does not account for the effect of natural disasters on distress migration, which has been found to temporarily increase migration in some regions, though typically does not lead to a sustained change in migration patterns [6]. Third, while we investigate the impact of top-down government interventions, we do not explore informal, bottom-up risk-sharing mechanisms that farmers themselves may employ to secure livelihoods in the face of increasing risk [49]. Fourth, we do not investigate the ramifications of livelihood decisions and the policies that influence these on local food security, which may be a prevailing concern in many subsistence farming communities in South Asia [50].

Nevertheless, through a novel agent-based model, we illustrate how risk aversion, financial restrictions, and climate impacts are likely to impact decision-making across a portfolio of livelihood strategies that are commonly employed in South Asian farming communities. We demonstrate that the intersection of these factors is likely to limit household adoption of higher-risk, higher-reward strategies, particularly the use of migration as an adaptation strategy, across a range of potential combinations of climate risk and community risk preferences. Consequently, future climate change is likely to lower average community incomes and increase inequality, absent any policy interventions. While the relative effectiveness of specific interventions vary based on community risk aversion and climate risk exposure, a package of cash and risk transfer mechanisms is robust across the range of model assumptions and parameter values tested here in its ability to increase community income and reduce inequality.

## 4 Methods

In line with modular and pattern-oriented approaches to ABMs [21, 31], this model is arranged into four layers that progressively introduce more sources of complexity. In the first layer of our model, agents represent economically rational households who seek to maximize the expected utility from these strategies, subject to constraints imposed by their limited resources. The second layer incorporates bounded rationality properties, in which agents are assigned different risk attitudes and rely on their social networks for information. The third layer incorporates demographic parameters, in which agents are assigned different educational levels that correlate with wealth, risk attitudes, and accuracy of information. In the fourth layer, we add two distinct climate effects that impact the incomes derived from farming strategies: a general long-term decline in mean crop yields as mean annual temperature increases [40, 51–54], and the possibility of extreme droughts, which become more likely as mean temperatures rise [54–56].

### 4.1 Layer 1: Economically Rational Optimization

Households select the strategy that maximizes their utility over a given time horizon  $h$ , on condition that the household savings  $S_i(t)$  exceed the cost of the selected strategy. The profit of household  $i$  employing strategy  $k$  in the strategy set  $\mathcal{K}$  is given by  $\pi_i^k(t) = I_i^k(x^k, t) + R_i(x^k, t) - C_i^k(t)$ , where  $I_i^k(x^k, t)$  represents the income corresponding to strategy  $k$  with  $x^k$  on-farm household members,  $C_i^k(t)$  represents the cost of strategy  $k$ , and  $R_i(x^k, t)$  represents the remittances received from migrants. According to modern portfolio theory, we construct the utility function as the difference of expected profit and profit volatility

$$U(\mu_i^k(t), \sigma_i^k(t)) = \mu_i^k(t) - b_i \cdot \sigma_i^k(t), \quad (1)$$

with  $\mu_i^k(t) = \mathbb{E}[\pi_i^k(t)]$  and  $\sigma_i^k(t) = \sqrt{\mathbb{E}[(\pi_i^k(t) - \mu_i^k(t))^2]}$  the expected value and standard deviation of strategy  $k$  perceived by household  $i$  at time  $t$ , and  $b_i$  the risk weighing of household  $i$ . The decision-making process of a rational household can be formulated as the following optimization problem

$$\begin{aligned} \operatorname{argmax}_k \quad & \sum_{t=t_0}^{t=t_0+h} \frac{U(\mu_i^k(t), \sigma_i^k(t))}{(1 + \rho)^{t-t_0}} \\ \text{s.t.} \quad & C_i^k(t_0) \leq S_i(t_0), \end{aligned} \quad (2)$$

where  $\rho$  represents the discount rate in evaluating strategy costs and payoffs and  $S_i(t) = S_i(t-1) + \pi_i^k(t-1)$  represents the wealth of household  $i$  at time  $t$  (measured in liquid savings). In the first layer of the model, each household  $i$  has perfect information about the future income distributions of each strategy  $k$ , corresponding to unbiased values of  $\mu_i^k(t)$  and  $\sigma_i^k(t)$ . Moreover, in Layer 1 households only maximize expected profit, and for that

reason  $b_i = 0$ .

The set of strategies  $k$  available to farming households is {BAU; Diverse; Migrate}, each with its own expected income, risk, and cost. BAU farming is largely for subsistence with limited expected potential for income generation but also low costs  $C^{\text{BAU}}$ . Alternatively, farmers can diversify to other crops that may generate commercial income  $I^{\text{Diverse}}$ , but are also likely to come with higher initial costs  $C^{\text{Diverse}}$  and a higher income variance. Finally, households can send a migrant to an urban location; this has an up-front cost  $C^{\text{Migrate}}$ , but households can subsequently benefit from remittances. Incomes derived from the two farming strategies, BAU and Diverse, vary across households according to a Weibull distribution, while incomes from Migrate vary according to a log-normal distribution, based on a best fit with data available from the Nepal CVFS Labor Outmigration, Agricultural Productivity, and Food Security survey [35]. Costs related to BAU and Diverse strategies are taken from a survey on Costs and Returns of Grain and Vegetable Crop Production in Nepal's Mid-Western Development Region [36], and Migrate strategy costs are approximated as an average of migration costs from Nepal to India and Gulf countries [37]. In all cases, an important feature of the income distributions is that a few agents earn relatively high incomes, while the majority of agents receive less than the mean income. We incorporate two economic feedbacks in the Base Case Layer. First, we assume that when a household sends a migrant to the city, the remaining members continue farming using either the BAU or Diversification strategy. However, migration reduces the amount of labor available for farming, and therefore farm productivity declines according to a saturation function (Supplementary Information, Section 2.1). Similarly, we assume that payoffs from migration tend to exhibit decreasing marginal returns as a function of the number of migrants from the same household. More information about the specific utility, Weibull and lognormal functions used for this layer, as well as the Base Case parameter values used to initialize the model, can be found in SI, Section 2.1.

## 4.2 Layer 2: Bounded Rationality and Social Network Impact

The behavioural psychology literature has established several mechanisms through which decision-makers deviate from rational (*homo economicus*) behaviour assumed in Layer 1. Layer 2 (Bounded Rationality and Social Network Impact) seeks to account for this behaviour by relaxing some of the assumptions made in Layer 1. In this layer, households optimize expected profit corrected for profit volatility across the strategy set  $\mathcal{K}$ . This is consistent with empirical and theoretical literature from the field of new economics of labor migration, which views migration as one way in which households spread risk and smooth consumption across highly variable economic conditions [57, 58]. Households may differ with respect to the relative weight  $b_i$ , such that a higher value of  $b_i$  indicates a lower willingness to trade-off risk for expected return [59]. For Layer 2, we assume agents are randomly assigned a risk weighting from a normal distribution, with mean parameter value  $\bar{b}_i = 0.5$ , indicating that on average they penalize the perceived profit volatility of a

strategy with half the weight they assign to its expected profit.

In the bounded rationality layer, households use imperfect information about the income distributions, resulting in biased values of the expected income and income standard deviation. Households rely on a combination of their own bounded memories, limited social networks, and partial access to public sources to collect information about strategy incomes. Public sources are assumed to provide perfect information. To simulate information flow across limited social networks, each agent is assigned a set of network connections that define the peers with which it compares income and gathers information about alternative strategies. The number of connections for each household follows a power law distribution such that a few households have a high number of connections and serve as key hubs of community information, while most agents have only a few connections (Supplementary Information, Section 2.2). Household social connections alter the decision-making process in three ways. First, households must pass a status quo threshold before evaluating whether to change strategies. This test consists of comparing the household current profit with a reference point that accounts for the profits earned by their social connections and their own profits in recent years. Households that perceive they are below this reference point are motivated to re-evaluate their strategy, consistent with empirical research that points to the perception of relative deprivation compared to one's neighbors as a key migration push factor [60]. If the status quo threshold is passed, a second way in which social connections influence the household behavior is by altering the perception of expected strategy profit  $\mu_i^k(t)$  and standard deviation  $\sigma_i^k(t)$ . We assume that households balance imperfect information received from their social networks and their own memories with perfect information from public sources (e.g. government or media sources), which they weigh with factor  $\omega_i$ . Finally, a third way in which social connections influence the decision-making is by reducing migration costs. Empirical studies in several migration contexts have established that potential migrants are significantly more likely to migrate with increasing connections to current or returned migrants [48, 61]. Section 2.2 in SI contains more details on how each of these three feedbacks is operationalized.

### 4.3 Layer 3: Demographic Stratification

In previous layers, households were assumed to share similar demographic characteristics, and important parameters such as starting wealth, risk preferences, and weighting of public information sources were randomly distributed. However, demographic variables, especially educational attainment, have significant correlations with the ability to process information and adapt to climate risks [62, 63], and assumptions regarding these variables significantly impact projections regarding the future composition of societies [64]. While this model does not seek to account for all sources of demographic heterogeneity, Layer 3 accounts for variation in one of these variables - education - and its correlation with several parameters of interest to the model.

The effect of education is operationalized in the demographic stratification layer by assigning each household an educational attainment level  $E_i \in \{\text{Primary (representing no education - completed primary), Secondary (representing some secondary - completed secondary), Tertiary (representing any post-secondary education)}\}$ , consistent with categorizations that are typically used in population projections [64]. For simplicity, these educational levels remain constant over the course of the simulation run. While attainment may differ between male and female heads of household, and between parents and their children, it is assumed in this model that the highest education level of any household member is the most relevant for shaping future livelihood decisions.

In this layer, the education parameter  $E_i$  is correlated with the following parameters: Initial savings,  $S_i(0)$  (positive correlation), [65]; Risk weighting factor,  $b_i$  (negative correlation) [66, 67]; and weight given to public information on strategy payoffs,  $\omega_i$  (positive correlation) [68]. Table 3 in Section 2.3 of the SI displays the specific values used to parameterize the effects of education on these variables.

#### 4.4 Layer 4: Climate Stress

In the previous layers, the agricultural community experiences a stationary income distribution for each strategy  $k$ . In the climate stress layer, we relax the assumption of income stability over time to better reflect the potential impact of increasing climate risk on farming-based livelihoods [2, 40]. We do this by introducing two related climate phenomena: the effect of long-term change in mean temperature on crop yields [40, 51–54], and the impacts of increasing frequency of extreme events (e.g. droughts) on crop yields [54–56].

The first climate phenomenon assumes that the annual mean temperature of the agricultural community increases linearly between 2020 and 2050. While the rate of change in global mean temperature is projected to be non-linear over long time horizons, a linear rate of change is a fairly accurate approximation over shorter timeframes [69]. For the representative South Asian farming community in this model, we assume an average decrease in crop yield of 10 percent for every  $1^\circ\text{C}$  of warming, consistent with the observed global average impact of temperature increases on cereal crop yields in this region [40]. This effect is operationalized by adjusting the mean annual income of the BAU and Diversification strategies as a function of temperature (for more details, see SI Section 2.4).

In addition to a gradual decrease in the viability of farming strategies, increasing climate change may also threaten agricultural livelihoods through an increase in the frequency of catastrophic natural disasters, e.g. droughts [54–56, 70]. Thus, smallholder farmers may make adaptation decisions not only in response to long-term trends, but also to cope with more frequent shocks to their livelihoods. To account for this possibility, a second climate phenomenon represents the possibility of increasingly frequent natural disasters that may more drastically affect income from farming-based strategies. This effect is modelled using

a peaks-over-threshold approach under a non-stationary distribution. First, we employ the Standardized Precipitation and Evapotranspiration Index (SPEI) to establish a distribution and threshold for extreme droughts. The SPEI is a normalized index based on historical data (ranging from 1901 to present day) in which 0 represents the mean hydrological balance for any region in a given month, and increases/decreases of 1 unit represents one standard deviation in the historical distribution of the monthly hydrological balance [41]. We assign an SPEI value of -2 as threshold for an extreme drought for BAU crops, historically representing a 1-in-40 year drought event that would likely wipe out most of the crop yield in a particular growing season. We assume that cash crops used in the Diversification strategy are more water-dependent and thus more sensitive to drought risks in rain-fed agricultural areas; we use an SPEI value of -1.5 to delineate an extreme drought for this strategy (roughly historically equivalent to a 1-in-15 year drought).

In each timestep of the model, we assign the community an SPEI number by randomly sampling from the SPEI distribution. We account for the effects of changing mean annual temperature on the distribution of SPEI (non-stationarity) by regressing the lowest SPEI 3-month index in each year of the SPEI dataset (1901-2014) on mean annual temperature for the  $0.5^\circ \times 0.5^\circ$  grid cell that contains Bharatpur, in Nepal's Chitwan Valley. Thus, the probability of drought increases over time with increasing temperature, but does so differently for the BAU and Diversification strategies, given their different thresholds. More information on regressions used to relate temperature and SPEI are available in the SI, Section 2.4.

## **4.5 Policy Interventions**

We model the impact of three types of policy interventions - cash transfers, index-based insurance, and a remittance bank - on household strategy choices, community outcomes, and social utility. In addition to assessing the effects of these specific policy interventions, this section also allows us to more broadly compare strategies that mostly target the expected income of strategies (cash transfers) vs. strategies that mostly target the volatility of strategies (index insurance and the remittance bank). Details on the modelling of each of these three interventions are presented below.

### **4.5.1 Cash Transfer**

In the Cash Transfer intervention, we model an unconditional transfer of funds from the Nepali government to farming households. Households are given these funds at the beginning of every cropping cycle, and make decisions on their preferred strategy options knowing that they will receive such a transfer. When receiving information on the incomes of their social network, households also discount for this cash transfer in forming perceptions of strategy income. In this analysis, we model a cash transfer of 30 USD/household/cycle, in line with other forms of cash transfers that have been introduced in Nepal [47, 71] and

also roughly equivalent to the current levels of government subsidies for index insurance [45].

#### 4.5.2 Index-Based Insurance

Index-based insurance is a specialized form of insurance that gives policyholders a pre-specified payout based on whether a measurable index exceeds a threshold (e.g. a specific wind speed or drought indicator), as opposed to indemnity insurance, which pays each policyholder based on the assessed level of damages sustained. In this analysis, the index-based insurance uses the 3-month SPEI value as the indicator. This indicator is a random variable with a non-stationary probability distribution, as detailed in Section 4.4. In each cropping cycle, a random draw is taken from this distribution; if the value is lower than the BAU and/or Diverse drought threshold ( $\tau^{BAU} = -2.0$ ;  $\tau^{Diverse} = -1.5$ ), then the insurance policy is triggered and policyholders are automatically paid the expected loss for their crops in a drought event. Expected losses are calculated as a function of the mean income derived from each type of crop, which is also a non-stationary distribution based on long-term climate impacts on yields

$$L^k(t) = \mu^{I_k,nd}(t) - \mu^{I_k,d}(t), \quad (4)$$

where  $\mu^{I_k,nd}(t)$  represents the mean income for strategy  $k$  at time  $t$  in a non-drought year, and  $\mu^{I_k,d}(t)$  represents the mean income for strategy  $k$  at time  $t$  in a drought year. In every time step, each household farming BAU or Diverse crops has the option of purchasing an insurance policy for that crop cycle. Premiums are set at actuarially-fair values, and to establish a comparison to the cash transfer intervention, we assume that a government subsidises premiums by 30 USD/cycle. For comparison, the Nepali government currently subsidizes such premiums by 75 percent, which is approximately equal to 26 USD/ha/cycle for rice paddy, and 23 USD/ha/cycle for wheat [45].

Let  $I^{subs}$  represent the government subsidy, then premiums  $C^{k,pr}(t)$  are calculated at each time step  $t$  as

$$C^{k,pr}(t) = p^k(t) \cdot L^k(t) - I^{subs}, \quad (5)$$

where  $p^k(t)$  represents the probability of a drought for crop  $k$  at time  $t$ . Because households assign different weight to public information, they form their own different perceptions of  $p^k(t)$  and  $L^k(t)$ . In addition to different levels of wealth at any time  $t$ , this leads to different decisions among households about whether to purchase insurance. Under perfect information, households opting for insurance see the expected income  $\mu^{I_k}(t)$  from farming strategy  $k$  and volatility  $\sigma^{I_k}(t)$  of these strategies adjusted as follows

$$\begin{aligned} \tilde{\mu}^{I_k}(t) &= (1 - p^k(t)) \cdot \mu^{I_k,nd}(t) + p^k(t) \cdot (\mu^{I_k,d}(t) + L^k(t)) = \mu^{I_k,nd} \\ \tilde{\sigma}^{I_k}(t) &= (1 - p^k(t)) \cdot \sigma^{I_k}(t). \end{aligned} \quad (6)$$

The perfect information on the income distribution is combined with social information and information from memory to yield the perceived income distribution, expressed by  $\tilde{\mu}_i^{I^k}(t)$  and  $\tilde{\sigma}_i^{I^k}(t)$  (SI, section 2.2). More details on the decision-process to acquire index-based insurance can be found in the SI, section 2.5.

### 4.5.3 Remittance Bank

While the Migrate strategy leads to a relatively high expected income, it also is characterized by high volatility, which may dissuade some households from adopting this strategy. As one intervention to make this strategy more attractive, we model a hypothetical remittance bank that reduces income volatility for this strategy by pooling a portion of migration remittances from households in the community. Under this policy, all households engaging in migration deposit a specified proportion  $\rho^{\text{rem}}$  of their remittances in each cycle (for this analysis, we set  $\rho^{\text{rem}} = 0.25$ ). The bank then pays each migrating household the same proportion  $\rho^{\text{rem}}$  of the expected remittance income for the number of migrants in a household. To establish a comparison with the cash transfer and index insurance, we assume that a government subsidizes deposits to the remittance bank by a remittance subsidy  $R^{\text{subs}}$  of 30 USD/cycle. In each cropping cycle, a household deposit to the bank  $R_i^{\text{dep}}(x_i, t)$  and receives a payout from the bank  $R_i^{\text{po}}(x_i)$ , which are defined as

$$\begin{aligned} R_i^{\text{dep}}(x_i, t) &= \rho^{\text{rem}} \cdot R_i(x_i, t) \\ R_i^{\text{po}}(x_i) &= \rho^{\text{rem}} \cdot \mu^R(x_i), \end{aligned} \quad (7)$$

where  $R_i(x_i, t)$  is the random income for a household engaging in migration (scaled by the number of migrants per household  $x^{\text{hh}} - x_i$ , with  $x^{\text{hh}}$  the household size) and  $\mu^R(x_i)$  is the expected income for this strategy for a given number of migrants per household. For simplicity, under the Remittance Bank policy intervention, we assume all households engaging in migration participate in such a remittance bank. Similar to the effects of index insurance for the farming strategies, the presence of a remittance bank adjusts the expected income and standard deviation of Migrate as follows

$$\begin{aligned} \tilde{\mu}^R(x_i, t) &= (1 - \rho^{\text{rem}}) \cdot \mu^R(x_i) + \rho^{\text{rem}} \cdot \mu^R(x_i) = \mu^R(x_i) \\ \tilde{\sigma}^R(x_i, t) &= (1 - \rho^{\text{rem}}) \cdot \sigma^R(x_i), \end{aligned} \quad (8)$$

where  $\sigma^R(x_i)$  is the standard deviation of the Migrate income distribution in the absence of a Remittance Bank.

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